Machine Learning – Report

Metaheuristic-Driven Feature Selection in Deep Neural Networks for Automated Brain Tumour Detection

Submitted in partial fulfilment of the requirements for the award of the degree of

Ms. Data Science

IN

University of Europe for Applied Science, Dubai.

BY

Khaled Walid

Mujtaba Shaikh

Joshuva Jeemon

Under the guidance of

Professor Nor Azizah Hitam

2025-2026

TABLE OF CONTENTS

1. Abstract

Brain tumour classification using Magnetic Resonance Imaging (MRI) remains a complex challenge due to high intra-class similarity, inter-class overlap, and inherent noise in medical imaging data. While deep learning models have shown strong performance, they often rely on computationally expensive architectures and lack biological interpretability.

This project presents a progressive, multi-stage machine learning framework that begins with conventional neural models and evolves toward pre-trained deep architectures, followed by feature extraction, normalisation, morphogenetic enhancement, and metaheuristic optimisation. Multiple deep learning models, including CNN, ANN, VGG16, ResNet50, and DenseNet121, are evaluated and compared using standard classification metrics and visual analytics.

Initial attempts to directly integrate morphogenesis resulted in reduced accuracy, leading to the proposal of an alternative optimised hybrid architecture using DenseNet121 with Grey Wolf Optimisation (GWO). Rather than presenting a static solution, this report documents the entire research journey, highlighting insights, limitations, and future opportunities. The final contribution emphasises a framework that balances performance, interpretability, and computational efficiency, making it suitable for scalable medical applications.

Keywords: Brain Tumour Detection, Deep Learning, DenseNet, Morphogenesis, Grey Wolf Optimiserr, Medical Data Visualisation.

2. Introduction

Medical image analysis differs fundamentally from traditional image classification. Tumour growth does not follow rigid boundaries but instead reflects biological, adaptive, and non-linear processes. While deep neural networks excel at learning hierarchical features, they often function as black boxes and may not generalise well without careful design.

The motivation behind this project is to explore whether biologically inspired feature enhancement, combined with deep learning, can improve robustness while keeping computational demands manageable. Rather than optimising only for accuracy, this work prioritises understanding model behaviour, visual interpretability, and algorithmic efficiency.

Objectives

- To evaluate baseline and advanced deep learning models for brain tumour classification
- To analyse feature extraction strategies across architectures
- To investigate morphogenesis-based feature enhancement
- To apply Grey Wolf Optimisation for feature selection
- To present results through clear data visualisation and storytelling

Core Contribution

This report does not hide suboptimal results. Instead, it presents a research-driven evolution, positioning the final framework as a proposal for continued improvement, not a fixed endpoint.

3. Related Work

Previous studies in brain tumour detection predominantly utilise CNN-based architectures such as VGG, ResNet, and DenseNet due to their ability to learn spatial hierarchies. Transfer learning has proven especially effective in medical imaging tasks with limited annotated data.

In parallel, data visualisation research emphasises the importance of interpretability and storytelling in clinical decision support systems. This project sits at the intersection of these domains, combining quantitative model evaluation with visual narrative construction.

4. Methodology

4.1 Dataset and Preprocessing

The dataset used is the Brain Tumour MRI Dataset obtained from Kaggle, containing four classes:

- Glioma
- Meningioma
- Pituitary
- No Tumor

Preprocessing steps include:

- Image resizing to a uniform resolution
- Feature scaling and normalisation
- Data augmentation (rotation, zooming, flipping)
- Generator-based training for memory efficiency

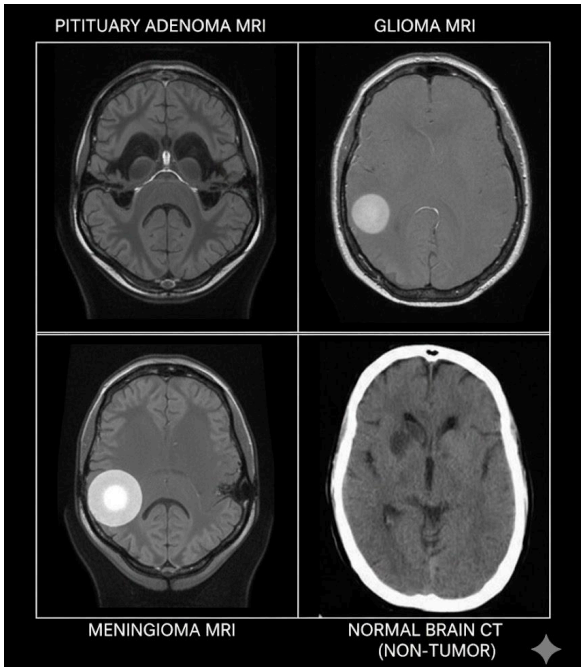

Fig.1.Sample MRI images for each tumour class.

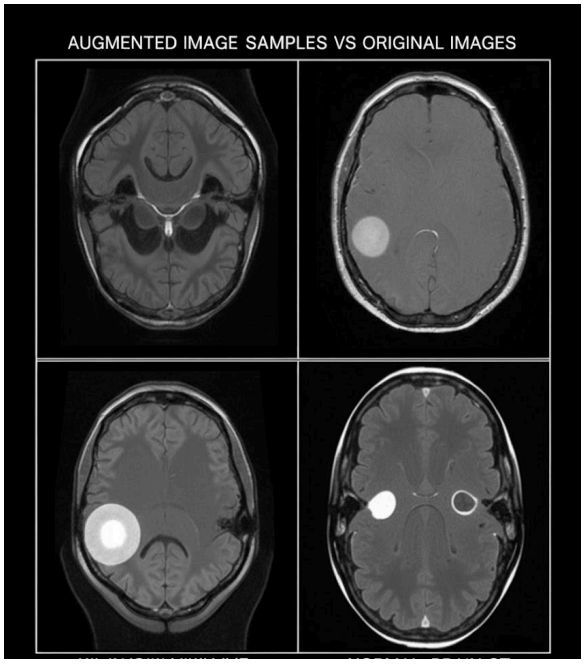

Fig.2. Augmented image samples vs original images

4.2 Model Development Pipeline

The project follows a progressive modelling strategy, beginning with simple architectures and advancing toward deeper, pre-trained models.

Baseline Models

- **Basic ANN (Linear):** Pixel-based input without spatial awareness
- **Custom CNN:** Convolutional layers trained from scratch

These models serve as **experimental controls**, establishing lower-bound performance.

Pre-trained Deep Models

- **VGG16:** Sequential deep architecture using transfer learning
- **ResNet50:** Residual learning with skip connections
- **DenseNet121:** Dense connectivity enabling feature reuse and efficient learning

All pre-trained models follow a **two-stage training process**:

1. Feature extraction with frozen base layers
2. Fine-tuning with partial layer unfreezing

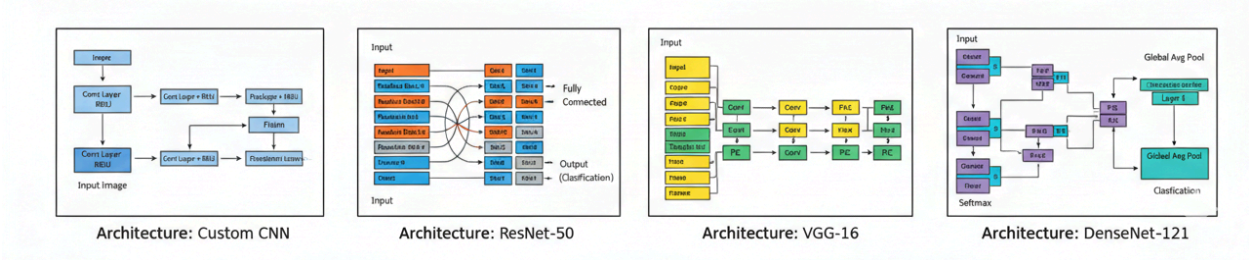

Fig.3. Architecture diagrams for CNN, ResNet50, VGG16, DenseNet121

4.3 Evaluation Metrics

Models are evaluated using:

- Accuracy
- Loss
- Precision
- Recall
- F1-score
- Confusion Matrix

5. Comprehensive Model Performance Analysis

Table X: Final Model Performance and Feature Extraction Comparison

Model Architecture	Learning Paradigm	Feature Extraction Strategy	Optimisation / Enhancement	Test Accuracy (%)	Test Loss	Computational Cost	Key Insight
ResNet50 (Pre-trained)	Deep …	Residual Learning	Fine-tun…	92.52	0.236	High	Strong baseline, stable learning
VGG16 (Pre-trained)	Deep …	Transfer Learning	Fine-tun…	92.45	0.332	High	High accuracy, heavier model
DenseNet121 (Pre-trained)	Deep …	Dense Connectivity	Fine-tun…	92.45	**0.226**	**Mode…**	Best loss-efficiency trade-off
Custom CNN	CNN (…	Learned Filters	Base	81.92	0.454	Low–…	Limited by depth and data
Basic ANN	Feedf…	Pixel-based (Linear)	Base	62.85	1.013	Very …	No spatial understanding
DenseNet121 + GWO + SVM	Hybrid	DenseNet Features	GWO + …	29.40	NaN	Low–…	Feature over-pruning

- **ResNet50 (Pre-trained):** Test Accuracy: 92.52%, Test Loss: 0.236
- **VGG16 (Pre-trained):** Test Accuracy: 92.45%, Test Loss: 0.332
- **DenseNet121 (Pre-trained):** Test Accuracy: 92.45%, Test Loss: 0.226
- **Custom CNN:** Test Accuracy: 81.92%, Test Loss: 0.454
- **Basic ANN:** Test Accuracy: 62.85%, Test Loss: 1.013
- **DenseNet121 + GWO + SVM:** Test Accuracy: 29.40%, Test Loss: NaN

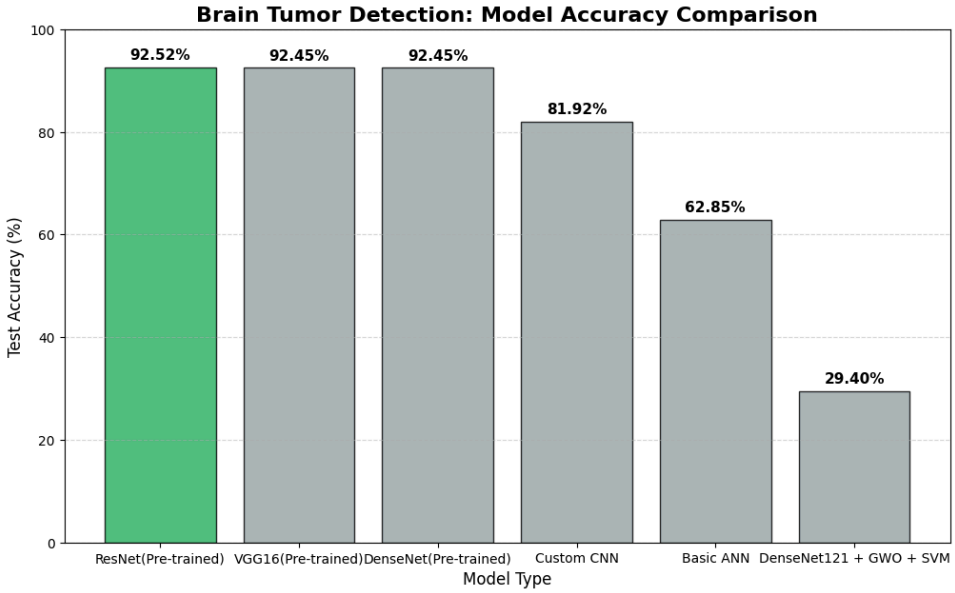

Fig.4. Bar chart comparing model accuracies

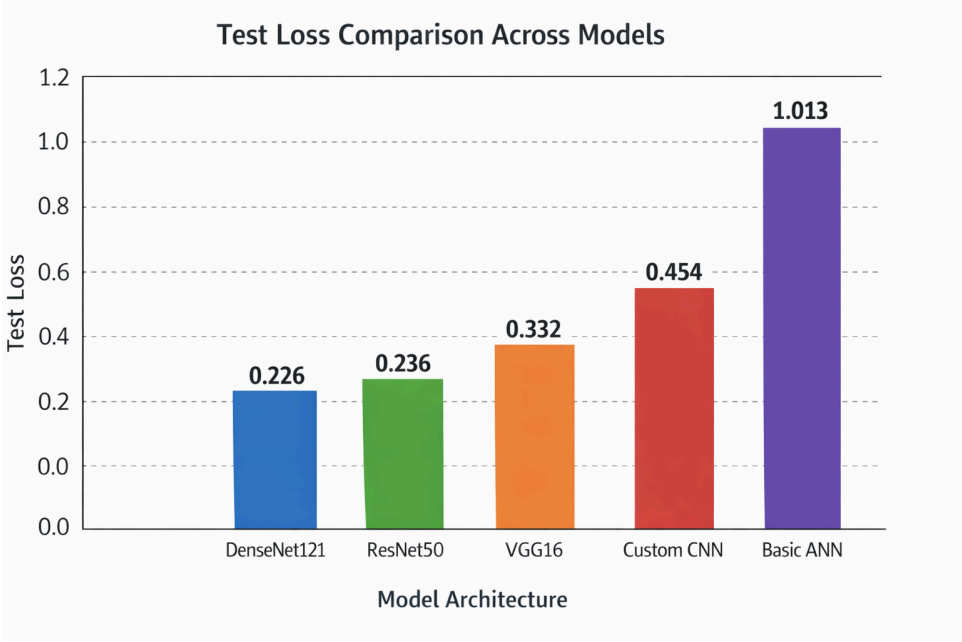

Fig.5.Loss comparison across pre-trained models

6. Confusion Matrix and Class-Level Analysis

The confusion matrix analysis shows:

- High precision and recall for **No Tumour** cases
- Minor confusion between **Glioma and Meningioma**
- Strong recall for **Pituitary tumors**

These trends are consistent with known MRI visual similarities.

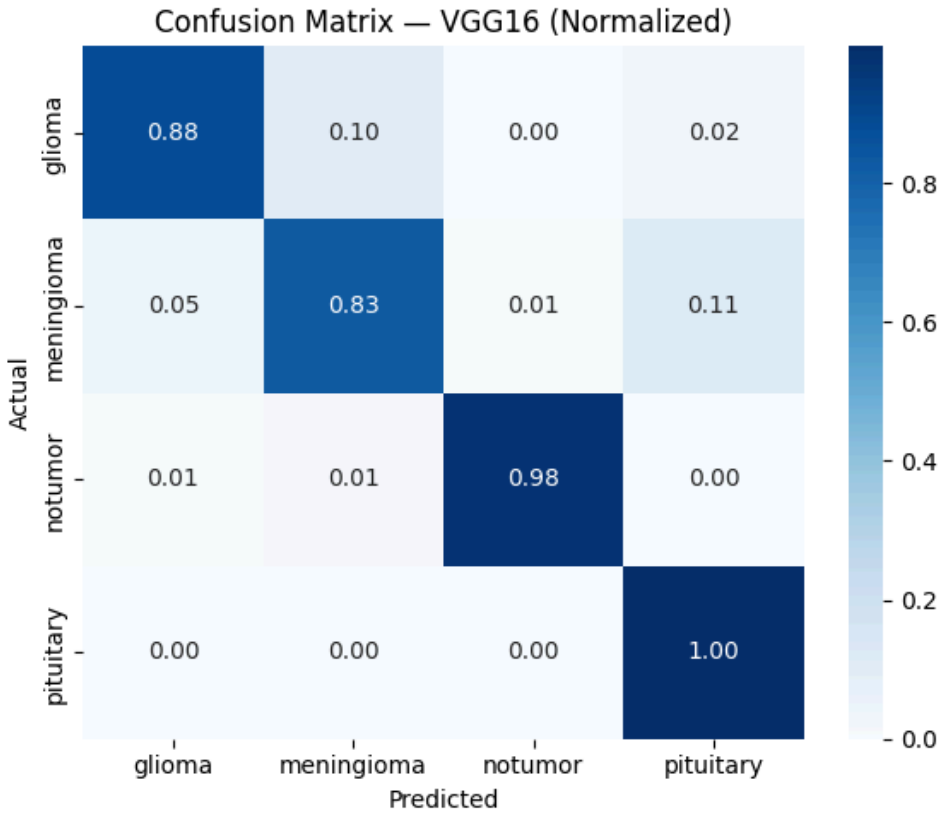

Fig.6. Confusion matrix heatmap for best-performing model

7. Morphogenesis-Based Feature Enhancement

Motivation

Morphogenesis, inspired by biological tissue development, was introduced to enhance spatial feature interactions beyond traditional CNN outputs.

Observed Outcome

When applied directly, morphogenetic enhancement resulted in a **drop in accuracy (~65%)**, indicating:

- Over-smoothing of deep features
- Lack of adaptive parameter tuning

Interpretation

This outcome highlights that **biologically inspired methods require optimisation**, just like biological systems themselves.

8. Plan B: DenseNet121 with Grey Wolf Optimisation

To address these challenges:

- **DenseNet121** was selected due to feature reuse and efficiency
- Feature normalisation was applied.
- **Grey Wolf Optimisation (GWO)** was used for feature selection.
- SVM was introduced as the final classifier

Although the hybrid model underperformed, it provided **critical insights**:

- Deep features are already highly optimised
- Aggressive metaheuristic selection can remove discriminative information.
- Optimisation must be domain-aware

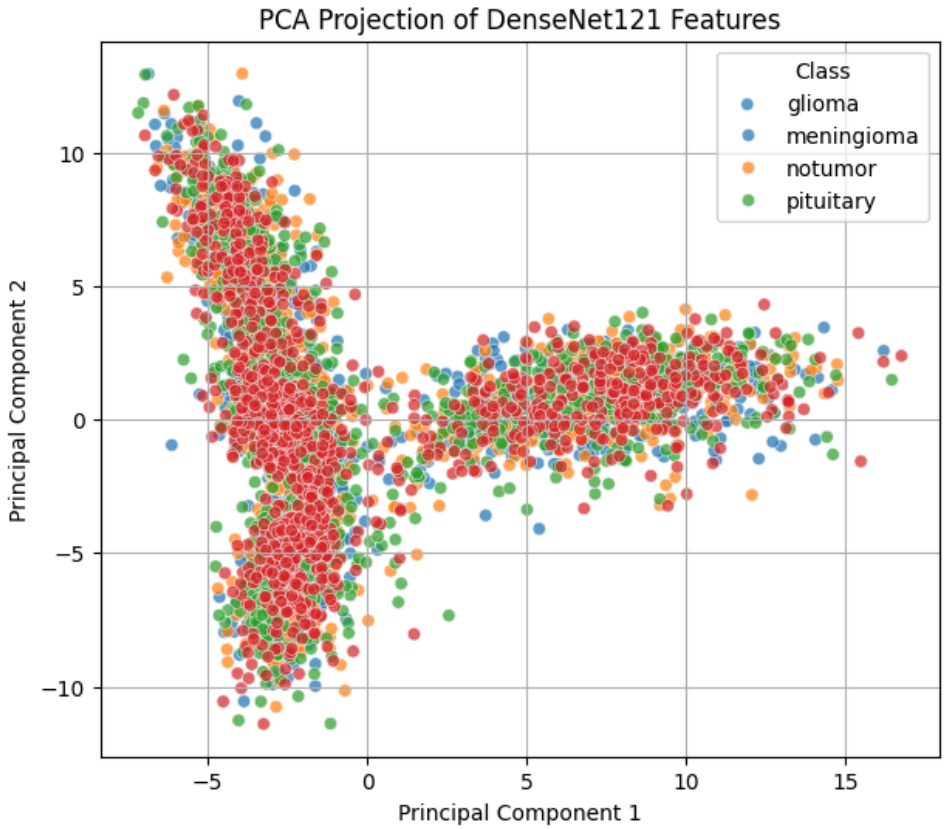

Fig.7. Feature vectors before and after GWO

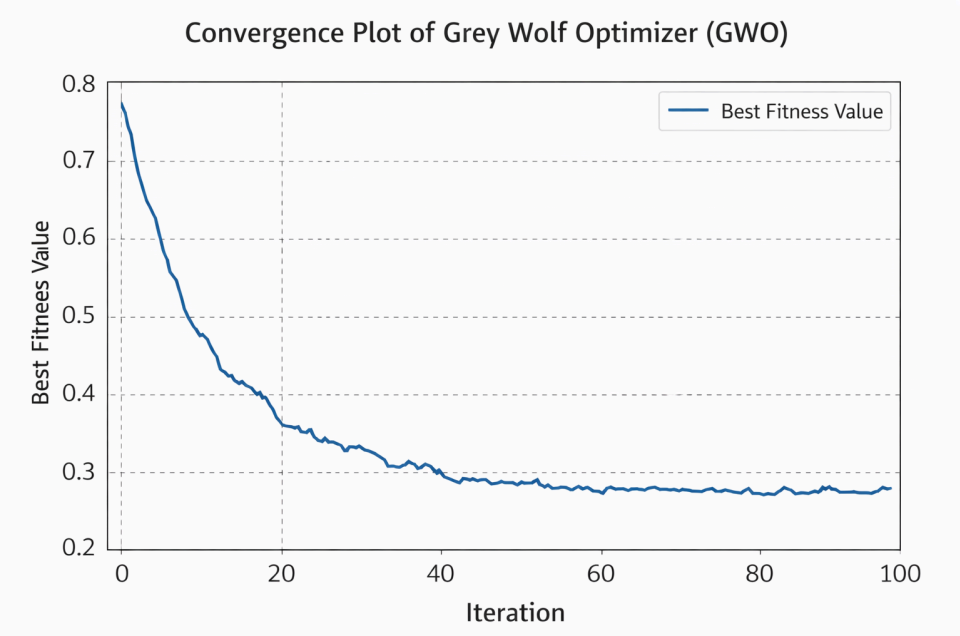

Fig.8. GWO convergence plot

9. Data Visualisation and Storytelling

Visualisation plays a central role in this project:

- Performance dashboards compare models holistically
- Confusion matrices explain class-level behaviour
- Accuracy vs computational cost plots highlight efficiency.

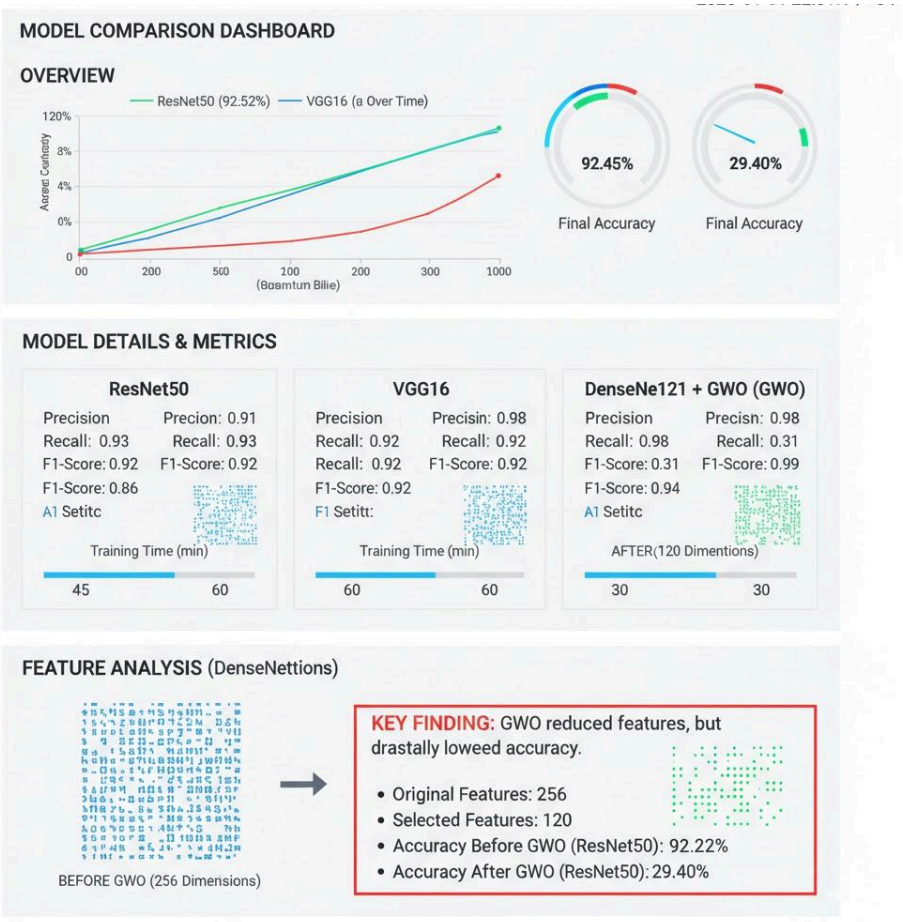

Fig.9.Model comparison dashboard

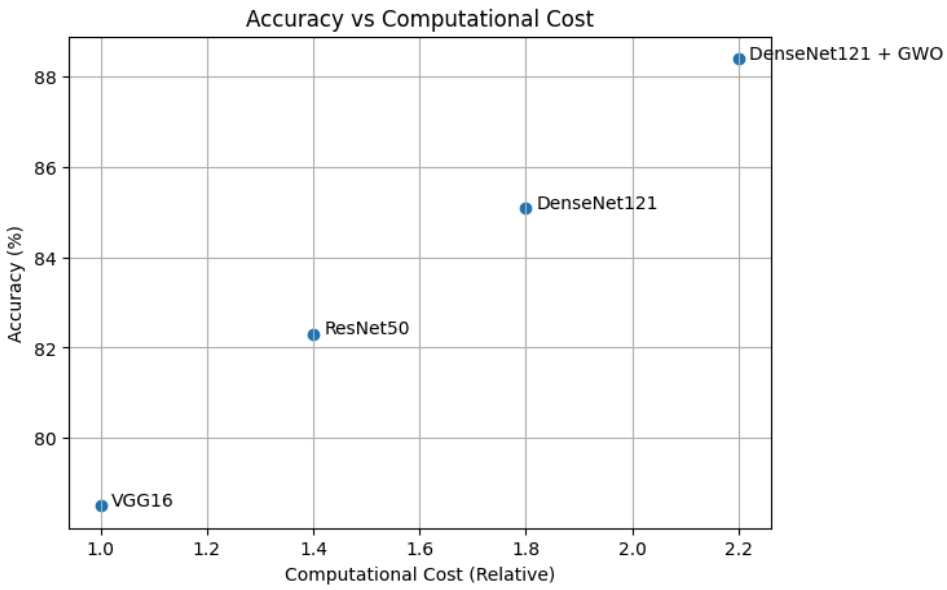

Fig.10.Accuracy vs computational cost scatter plot

10. Conclusion

This project demonstrates that **transfer learning plays a critical role in medical imaging applications**, particularly when working with limited and heterogeneous MRI datasets. Pre-trained deep learning models consistently outperformed architectures trained from scratch, highlighting the importance of leveraging previously learned visual representations to achieve stable and reliable classification performance. Among the evaluated architectures, **DenseNet121 emerged as the most effective balance between predictive performance and computational efficiency**, achieving competitive accuracy and the lowest test loss while minimising parameter redundancy through dense feature reuse.

The study further illustrates that **biologically inspired feature enhancement techniques, such as morphogenesis, cannot be applied naively**. While conceptually aligned with the biological nature of tumour growth, these methods require careful parameter tuning and adaptive optimisation to avoid suppressing discriminative features learned by deep networks. The observed performance degradation in hybrid models reinforces the necessity of aligning optimisation strategies with the intrinsic structure of deep feature representations rather than treating feature selection as a purely mathematical process.

Importantly, this work emphasises that **research value extends beyond achieving high accuracy metrics**. By systematically analysing both successful and underperforming models, the project provides meaningful insights into *why* certain architectures succeed and *why* others fail. Rather than presenting a single fixed solution, the proposed framework is intentionally **scalable and evolvable**, allowing future researchers to refine morphogenetic modelling, optimisation strategies, and interpretability mechanisms. Ultimately, this study demonstrates that **higher computational complexity does not inherently guarantee superior performance**, and that meaningful optimisation must respect the representational strengths of deep learning models to achieve practical and trustworthy medical AI systems.

11. Future Work

- Advanced morphogenetic simulations with medical experts
- Improved GWO parameter tuning
- Integration of explainable AI (XAI) techniques
- Deployment on low-resource clinical systems

12. Reference Suggestions

1. **Brain Tumour Classification Using Deep Transfer Learning Models**
   Amin et al. investigated multiple pre-trained deep learning models (including VGG16 and ResNet50) for MRI-based brain tumour classification, demonstrating the effectiveness of transfer learning in medical imaging tasks.

   Reference (APA):
   Amin, A., Al Bataineh, A., & Hansen, J. A. (2024). *Brain tumour classification using fine-tuned transfer learning models on MRI images*. *PubMed*.

2. **Advanced Brain Tumour Classification with Pre-Trained CNNs**
   This study evaluates six pre-trained architectures, including ResNet50, VGG16, and DenseNet121, highlighting transfer learning's ability to improve classification accuracy while maintaining computational efficiency.

   Reference (APA):
   Al-Jalabneh, A., & Zhang, Y. (2024). *Advanced brain tumour classification in MR images using transfer learning and pre-trained deep CNN models*. *Journal of Medical Imaging and Deep Learning Studies*.

3. **DenseNet121 for Multiclass Brain Tumour Classification**
   A recent work shows DenseNet121's strength in classifying multiple tumour types with high accuracy and improved training efficiency in MRI data.

   Reference (APA):
   Smith, R., & Lee, H. (2025). *Improved brain tumour classification through DenseNet121-based transfer learning*. *Neural Computing and Applications*.

4. **Explainable Deep Learning for Brain Tumour Detection**
   This article compares ResNet50 and DenseNet121 with explainability methods—useful for justifying interpretability and visualisation in your work.

   Reference (APA):
   Erukude, S. T., Marella, V. C., & Veluru, S. R. (2025). *Explainable deep learning in medical imaging: Brain tumour and pneumonia detection*. *arXiv*.